Using Social Media to Change Eating Habits without Conscious Effort

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Abstract
Healthy eating habits are important for modern people; however, sustaining these habits is often difficult because it requires a strong will. In this paper, we propose a social media system, Yumlog, that enables people to begin eating meals that are more healthful naturally and without conscious effort. Using the proposed system, users share information on their meals and evaluate the yumminess and healthfulness of each other’s meals. The satisfaction of a user with a meal increases with others’ positive evaluations. In behavioral science, this effect is called expectation assimilation. In addition, Yumlog modifies others’ evaluations, displaying evaluations of healthfulness as those of yumminess to the user consuming the meal. Thus, users tend to eat more foods that are evaluated as healthful foods and thereby, improve their eating habits without noticing it. We demonstrate the potential of the proposed system through user studies.

Author Keywords
Change of eating habits; social media; expectation assimilation; lifelog

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.
Introduction
With greater variety and availability of different foods, people need information regarding developing and maintaining healthful eating habits. Such habits are generally based on appropriate energy intake and a balanced diet. Although understanding this balance clarifies the appropriate types and amounts of food for healthful eating, the establishment of actual habits depends on the individual. However, some people who desire to improve their eating habits are unable to do so because they do not feel satisfied with the options available for healthful food.

If we can enhance the satisfaction of eating healthful meals, the stress of restraining our desire for unhealthful yet satisfying foods is relieved; consequently, healthful eating can become a satisfying habit. Our decisions are made not only according to personal preferences but also based on external information. Those tendencies in how we assess information are studied in psychological, behavioral, or cognitive science and are summarized as cognitive biases. The satisfaction found in a meal is influenced not only by the food itself, but also by external stimuli and information. In behavioral science, “expectation assimilation (EA)” refers to how the imagined palatability of a meal changes one’s perception of the actual meal [?].

The aim of this study is to examine an improvement in healthful eating habits that was achieved without restraining the desire for satisfying foods; this was achieved by offering people positive external information about a meal, which may unconsciously enhance satisfaction. In this research, we propose a social media for improving eating habits using EA with others’ responses.

Related Work
Unhealthful eating habits can result in a higher incidence of lifestyle-related diseases, including obesity, excessive fat in the blood, diabetes, and high blood pressure [?]. Self-control is generally necessary to improve eating habits. Quinn et al. demonstrated that in contrast to responses to temptations, bad habits were controlled most effectively through spontaneous use of vigilant monitoring [?]. The method of improving eating habits is based on maintaining balanced nutrition or energy intake; however, it is difficult to self-monitor these components, because self-monitoring requires calculations based on the nutritional information of a meal’s components.

To resolve the self-management problem, researchers have proposed methods that automatically estimate the energy or balance of meals. Aizawa et al. suggested a method that estimates nutrition using meal pictures [?]. Noronha et al. developed PlateMate, a system that allows participants to capture photos of their meals and receive estimates of the nutritional balance and composition [?]. When a participant uploads a photograph of his or her food, PlateMate crowdsources nutritional analysis from photographs using Amazon Mechanical Turk. These methods attempt to improve eating habits by estimating or managing the nutrition balance or energy intake without requiring any effort from participants; in other words, they clarify the importance of good eating habits by showing people how nutritious their daily meals are.

There have been many studies aimed at strengthening users’ wills and improving their habits using mobile devices in particular. Baumer et al. suggested that open-ended social awareness, making users aware of both others’ and their own decisions, might also serve as an effective central design principle for mobile health [?].
Patrick et al. showed that a text-message-based intervention might be a productive method of encouraging more healthful food choices or promoting behaviors [?].

Further, several recent works have demonstrated the value of social support for health. Grimes et al. developed EatWell, a system that allows users to create voice memories with their cell phones describing how they have tried to eat healthfully in their neighborhoods, and concluded by presenting implications for the design of future applications that facilitate the sharing of health-related experiences [?].

The gamification of health using mobile terminals is becoming popular. James et al. created a social computer game, Fish’n Steps, that links a player’s daily foot step count to the growth and activity of an animated virtual character, a fish in a fish tank, so as to promote an increase in physical activity [?]. Grimes et al. showed the promise of using casual mobile games to encourage people to adapt to lifestyles that are more healthful [?]. These studies used games to motivate users to improve their lifestyles. Systems such as FoodLog and PlateMate might not be suitable for many people whose wills to change their lifestyles are weak. On the other hand, enhancing healthful meals may be effective for such people.

The satisfaction derived from a meal is influenced not only by taste but also by external information. Wansink observed the EA phenomenon, where unconscious expectations of how satisfactory or appetizing a meal will be affected how appetizing it is [?]. He noted that something that was anticipated to be delicious was perceived as more delicious than something that was not anticipated to be delicious. Furthermore, Wansink et al. revealed many factors that influence food intake, such as package size [?], accessibility to foods [?], etc. They noted that the recognition of consumption volume is influenced by environmental factors that appear to lack any direct relation to meals; further, they suggested that the quantity that people eat or drink can be changed without their awareness, by inhibiting consumption monitoring and by suggesting alternative consumption norms [?]. Allison et al. also indicated that beer brand identification influences taste perception [?].

Our Approach
In this study, we aim to improve people’s eating habits by adding external information that unconsciously enhances satisfaction with a meal while the person is eating.

Many types of information, such as knowledge of where food is produced or bought or the reputation of a restaurant, can induce EA. Nevertheless, it is not always possible for this information to be applied to all foods uniformly. For instance, if a meal is cooked at home, it likely has no public reputation for quality. However, information on how appetizing other people think the meal appears can be added to all meals uniformly. Therefore, we selected others’ perception of a meal’s yumminess to develop our healthful eating programs.

In this study, we use social media to provide this information. Social media, which has become very popular in recent years, allows for information sharing in real time and can yield many responses quickly. This aspect of social media enables us to add evaluations and accumulate those of others. We consider that even when the meal contents are the same, EA induced through social media can change how appetizing a meal appears to people and their satisfaction with that meal. We designed and constructed a system that enables participants to add their evaluations of a meal and receive those of others.
Using information from the literature, we designed a means of enhancing people’s satisfaction with healthful meals through feedback from others and evaluated whether this method improves people’s eating habits.

**System Implementation**

We constructed a system, Yumlog, where people can share information regarding their meals. The system was developed natively for Apple Inc.’s iOS, with Python and MySQL on the server side. This server system works on Amazon Elastic Compute Cloud from Amazon Web Service. A database is constructed using Amazon Relational Database Service. Figure 1 illustrates the use of Yumlog, consisting of the following four stages: beginning of meal, evaluating others’ meals, viewing others’ evaluations, and end of meal. In Yumlog, photos of meals that are captured before eating are shared with other people. Users of Yumlog are sometimes a participant and at other times an evaluator. In this research, a participant means a person who eats an meal and shares it, and an evaluator means a person who evaluates a shared meal.

First, participants were instructed to photograph the meal with their smartphones before they began eating and upload it to our server; then the server distributed the photo to other participants.

Then, the participants who viewed the photographs anonymously evaluated how appetizing the meal appeared using a seven-point rating system (Figure 2). The evaluator views who eats and what he or she eats as a list and can add open-ended comments. Items are deleted automatically from the list when a meal ends. These evaluations were anonymous, because some evaluations may be disregarded if participants can identify the evaluator.

![Figure 1: Flow chart of Yumlog use.](image)
The evaluations of others were presented in real time to a participant eating the meal (Figure 3). Others’ evaluations, the number of points, and their comments are listed. When a user finishes eating a meal, he or she must record satisfaction with the meal.

Although using others’ evaluations of meals and our method of assessing meal satisfaction are both subjective, they have often been used in studies on meal satisfaction. Adachi et al. split satisfaction with meals into five factors: environmental, material, taste-sensation-related, mental, and physical [?]. Furthermore, the material factor was divided into two factors, quantity, and quality. From these factors, they used the following six: the yumminess, enjoyment, desire, amount, expectation, and atmosphere of a meal. Okamoto et al. added “satisfaction after a meal” to these factors and defined satisfaction with the meal as the sum of the seven items’ points [?].

In this research, we adopted seven factors for evaluating satisfaction with meals. After eating a meal, a participant answers seven questions on a seven-point scale, with scores ranging from -3 to +3; the sum of the scores for these questions, ranging from -21 to +21, represented the person’s satisfaction with the meal. The questions were

1. Yummy?
2. Enjoyable?
3. Good menu?
4. Good atmosphere?
5. Good amount?
6. Satisfied?
7. Were you looking forward to the meal?

User Study

We predicted that enhancing satisfaction with healthful meals would be an effective method of changing the eating habits of participants. We assumed that the feeling of satisfaction with healthful meals would be enhanced, when the participants expected healthful meals to be appetizing, owing to EA. Therefore, besides rating how appetizing it appeared, we also requested the participants to evaluate how healthful the meal appeared on another seven-point rating scale, with scores ranging from -3 to +3. The evaluation of healthfulness was given to participants in the same manner as the evaluation of how appetizing a meal appeared. An evaluation of a meal that was actually evaluated as healthful was displayed to participants as appetizing (Figure 4).

After this experiment, another experiment that did not use the secret change in the evaluations was added, so we could compare evaluations of healthfulness and yumminess.

The healthfulness of meals was not evaluated nutritionally, but we guessed that the evaluations should approach the appropriate value as more evaluations were accumulated. For instance, in PlateMate, the estimated ingredients become close to the true quantities when the number of evaluators increases.

Experimental Procedure

We requested ten participants to use Yumlog, and we manipulated the evaluations. Participants evaluated each other’s meals by answering “How healthful does it look?”, “How yummy does it look?”, and “How satisfying does it look?”. The responses to the first question were presented to users as an evaluation of how appetizing the meal was, and the others are dummy questions so that participants would not suspect the secret change. After users ended a
meal, they evaluated their satisfaction with the meal on a seven-point scale of seven items.

In addition, the system generated dummy evaluations automatically depending on the real evaluations of healthfulness to confirm EA phenomenon. After the system waits until a real evaluation is added, it randomly selects values for two evaluations, how yummy and how satisfying the meal appears, from $-3$ to $+3$. A dummy evaluation of healthfulness is based on the average of the real evaluations of healthfulness. The dummy evaluation is randomly selected among the rounded average and its before and after. However, the maximum value is $+3$ and the minimum value is $-3$.

We performed two correlation analyses. $R_h$ was the correlation between meal satisfaction and the manipulated evaluations, and $R_t$ was that between meal satisfaction and the real evaluations. If $R_h$ is greater than $R_t$, this manipulation was effective in enhancing the satisfaction attributed to healthful meals. We conducted a time series analysis of participants’ meal choices to examine whether the healthfulness of participants’ meals improved. After the experiment, we requested the participants to complete questionnaires and investigated the subjective changes.

Result

In this study, the experiment lasted three weeks and included 179 meals, for which 1,208 evaluations were received. 10 subjects participated in this study: seven men in their twenties, a man in his thirties, and two women in their twenties. The results of the correlation analyses are displayed in Table 1.

<table>
<thead>
<tr>
<th>User</th>
<th>Meals</th>
<th>$R_h$</th>
<th>$R_t$</th>
<th>$R_h &gt; R_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>35</td>
<td>0.914</td>
<td>–</td>
<td>True</td>
</tr>
<tr>
<td>B</td>
<td>15</td>
<td>0.753</td>
<td>–</td>
<td>True</td>
</tr>
<tr>
<td>C</td>
<td>27</td>
<td>0.814</td>
<td>–</td>
<td>True</td>
</tr>
<tr>
<td>D</td>
<td>12</td>
<td>0.794</td>
<td>–</td>
<td>True</td>
</tr>
<tr>
<td>E</td>
<td>9</td>
<td>0.785</td>
<td>0.912</td>
<td>False</td>
</tr>
<tr>
<td>F</td>
<td>29</td>
<td>0.600</td>
<td>0.502</td>
<td>True</td>
</tr>
<tr>
<td>G</td>
<td>21</td>
<td>–</td>
<td>0.783</td>
<td>False</td>
</tr>
<tr>
<td>H</td>
<td>12</td>
<td>–</td>
<td>–</td>
<td>False</td>
</tr>
<tr>
<td>I</td>
<td>8</td>
<td>0.922</td>
<td>–</td>
<td>True</td>
</tr>
<tr>
<td>J</td>
<td>11</td>
<td>0.898</td>
<td>–</td>
<td>True</td>
</tr>
</tbody>
</table>

Table 1: The number of meals and correlation coefficients; non-significant results are denoted by –.

For seven of the participants (A, B, C, D, F, I, and J), $R_h$ was greater than $R_t$. Therefore, when evaluations of the healthfulness of a meal were secretly changed to evaluations of its appeal, participants’ meal satisfaction was influenced by the evaluations of others. It is possible that the positive evaluations of others regarding the healthfulness enhanced their satisfaction with a healthful meal or that the negative evaluations of others lowered their satisfaction.

Next, we analyzed individual changes over time using ordinary least squares (OLS) regression. Figure 5 shows the collection of fitted trajectories expressing each user’s estimated intercept and slope in a linear change model. The average of the numbers of each user’s meals is approximately 17. Figure 5 represents the change in users’ eating habits in this experiment. Further, according to each user’s correlation coefficient between the average evaluation of healthfulness and the recorded numbers (time series), three users exhibit weak positive correlations ($R > 0.2$).
Although this method is used for a descriptive analysis of individual changes over time and is an efficient use of longitudinal data, data on the healthfulness of the meal are episodic data. Thus, it may not be adequate to focus on each meal. Therefore, in this study we focus on the frequency of healthful meals. We used time series analysis to examine the trends in the average of the evaluations of healthful appearance for each participant’s meal. According to the histogram (Figure 6) of the evaluations of how healthful a meal appeared, the median value was zero; therefore, we defined a meal whose average evaluations of healthfulness were greater than zero as a healthful meal. Five participants (A, D, E, I, and J) ate meals that were more healthful in the second half of the program, i.e., there was a tendency toward more healthful meals (Figure 7). For the other five participants, there was no change, though participants B, C, and F maintained comparatively healthful meals throughout the experiment.

We examined participants’ subjective impressions of their change in eating habits using a questionnaire. We requested the participants to list the changes they imbibed after using Yumlog. The answers are summarized below.

- The reported changes in meal components included such choices as
  - eating more colorful foods
  - trying to eat more vegetables or fruits
  - trying to eat meals that are more balanced
  - decreasing intake of instant foods
  - avoiding eating cup noodles

- The reported changes caused by seeing others’ meals included:
  - becoming curious about what others eat
  - becoming hungry when more than one person started eating
According to the responses to the questionnaire, participants’ awareness of healthful meals changed, and they tried to eat meals that are more balanced by incorporating more vegetables and fruits into their diet.

**User Study in the Real-World Context**

The previous experiments were designed under controlled circumstances, so this effect may be impractical. We examined an experiment that applied this method in the real-world context with a published application, “Table For Two (TFT)” to ensure practical effectiveness of this method.

**Experimental Design**

Users evaluate each meal by tapping a button, “Healthful” or “Yummy” and if they think it neither, they can skip it. Evaluations are feedback as points, “Healthful” and “Yummy.” We assigned users to two groups, Experimental or Control Group at random, and manipulated the points depending on the group. In the control Group, one evaluation becomes one point, in other words, the number of points means how many times the meal is evaluated. On the other hand, half of the “Healthful” points are added to the “Yummy” points in the experimental group. For example, when one meal is evaluated as healthful ten times and as yummy twelve times, the ten and twelve points are fed back, if the user belongs to the control group. On the other hand, if he or she belongs to the experimental group, five points are added to the yummy points (Figure 8). This manipulation makes the experimental group more satisfied when they eat healthful meals.

We compared the frequencies of healthful meals between the first and second halves of the study. We used $H$, defined as follows, as the standard of how healthful a meal is.

$$H = \frac{\text{healthful}}{\text{healthful} + \text{yummy} + \text{skip}}.$$  (1)

In this experiment, meals that are evaluated as more healthful than the median of each user’s meals are defined as healthful, because the healthfulness of users’ eating habits is individual.

**Result**

We analyzed data collected for 40 days after TFT had been released. 1,056 users shared 8,451 meals and 82,400 evaluations, including 43,085 skips. To omit noise, we ruled out meals that had received fewer than five evaluations and users who had shared fewer than ten meals. Finally, the control and experimental groups contained 64 and 81 users, respectively.

We compared between these two groups like A/B testing. That is because that there might be any influences which are caused by using this application. For example, Zepeda et al. suggested that recording meal logs might improve eating habits, and standards of evaluations could have changed in the experimental term [?]. Therefore we compared between them so that we exclude effects except for our method.

At first, we compared frequencies of healthful meals between the first and second halves. In the control group, 31 out of 64 users ate healthful meals more frequently in the second half than in the first. In contrast, in the experimental group, 49 out of 81 users improved their eating habits. Using a binomial test, we examined null-hypothesis that 49 out of 81 users accidentally improve when the occurrence probability of improvement is 31 out of 64. As a result, There is a significant difference between these groups ($p < .05$). Additionally, we calculated 95 percent confidence interval...
(Pearson-Cropper) :0.490 - 0.712. The lower threshold was bigger than 0.48435 (31 out of 64) and it illustrated that our method significantly improve eating habits.

Next, we compared medians of $H$ between the first and second halves, and paired t-tests were performed in each group (Figure 9). These comparisons showed a significant difference ($p < .01$) in the experimental group but no significant difference in the control group.

Discussion
These results indicate that others’ evaluations can change people’s eating habits by influencing their satisfaction with healthful meals. This effect appears not only in a controlled experimental environment but also in a freely published application.

In this experiment, the control group users did not improve eating habits in spite of the suggestion by Zepeda et al. that recording meal logs might improve eating habits. However, the users had recorded meal logs before the updating of TFT, so they might have improved already before this experiment started. In other words, there is a possibility that this method could enable those who have already improved eating habits by recording meal logs improve further.

Conclusion and Future Research
In this study, we developed a system, Yumlog, for sharing and evaluating meals where people share meal photos and have others evaluate in real time how appetizing the meal appears. We presented evaluations of healthfulness that were manipulated to enhance the desirability of food to see whether they changed participants’ meal satisfaction. Five of the ten participants improved their eating habits using Yumlog. Furthermore, the method of enhancing satisfaction with healthful meals was effective when it had been applied to a published application, TFT.

We want to consider how the identity of the evaluator affects participants as a future work. In our experiments, all the evaluations were anonymous to control for the possibility of this identity effect. However, participants’ opinions of the evaluator often influenced the importance they associated with an evaluation. Therefore, we wish to consider the strength of the connection between the evaluator and the participator according to the social graphs, and introduce weighting of evaluations as a new standard.

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